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DOI
10.1080/15435075.2024.2397020

Publication date
2024

Document Version
Final published version

Published in
International Journal of Green Energy

International Journal of Green Energy

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/ljge20

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To cite this article: Xinwei Ma, Yu Meng, Hongjun Cui, Long Cheng & Yufei Yuan (09 Sep 2024): What do battery electric vehicle (BEV) users think of the charging infrastructures launched in expressway service areas? Evidence from China, International Journal of Green Energy, DOI: 10.1080/15435075.2024.2397020

To link to this article: https://doi.org/10.1080/15435075.2024.2397020

Published online: 09 Sep 2024.

INTERNATIONAL JOURNAL OF GREEN ENERGY
https://doi.org/10.1080/15435075.2024.2397020

What do battery electric vehicle (BEV) users think of the charging infrastructures launched in expressway service areas? Evidence from China

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ABSTRACT

The emergence of electric vehicles (EV) presents new opportunities for transportation decarburization and sustainable transportation in cities worldwide. However, previous research has primarily focused on EV charging infrastructures within urban areas, with limited attention to those launched in expressway service areas. Addressing this gap is crucial in alleviating EV users' range anxiety on expressway journeys. This study investigates the BEV users' reuse behavior toward charging infrastructures on expressways. Focusing on the BEV users who had used the charging infrastructures on the expressway, the structural equation modeling and the multi-group analysis are employed to reveal the effect of psychological factors on BEV users' reuse intention and explore the heterogeneity across different socio-demographic groups. Results reveal that Attitude and Subjective Norm drive the reuse intention. Perceived Risk has an indirect negative effect on reuse intention. Attitude has a more significant effect on reuse intention among elder users, high-frequency users, and low remaining State of Charge (SOC) users. This paper offers new insights for charging infrastructures' planning and operation in expressway service areas.

ARTICLE HISTORY
Received 11 March 2024
Accepted 15 August 2024

KEYWORDS
Battery electric vehicle (BEV); charging behavior; charging infrastructures; expressway; psychological factors

1. Introduction

In 2021, global carbon dioxide emissions were approximately 39.32 billion tons, which increased by 5.7% from 2020 (SROWE, 2022). According to Jaiswal et al. (2021), about one-fourth of all greenhouse gas emissions worldwide are attributed to the transportation sector, and by 2030, emissions are expected to rise from 23% to 50%. The transportation industry is thought to be one of the main causes of climate change due to its consumption of fossil fuels and emissions of carbon dioxide (Pradeep, Amshala, and Raghuram Kadali 2021). In this context, transportation and environmental policymakers around the world pay attention to cleaner and greener vehicles (Bi et al. 2023). Electric vehicle (EV), offers the benefits of low energy consumption, quietness, and fewer pollutants (X. Zhang et al. 2022), therefore, increasing the market share of EVs is a potentially efficient way of decarbonizing road transport, improving urban air quality, and mitigating global warming (Potoglou, Song, and Santos 2023). Fortunately, EVs have been growing rapidly and globally in recent years, with EV stocks set to exceed 26 million by 2022, a 60% increase from 2021 and more than five times the stock in 2018 (International Energy Agency 2023).

China has the largest EV market globally, rising fast in both output and sales (Zheng et al. 2020). Battery electric vehicles (BEVs), one of the mainstream types of EV, have become the main choice of Chinese consumers due to their advantages such as high energy efficiency, low maintenance costs, and good driving experience. According to Peoples Network (n.d., the number of BEVs in China has reached 15.52 million, accounting for 76.04% of the number of EVs. With the improvement of BEV battery technology and energy storage system (Hou, Zhao, and Ge 2017; Liang et al. 2023; X. Zhang et al. 2021), the expressway travel demand of BEV users is increasing (Ge and MacKenzie 2022; Solvi Hoen et al. 2023). However, the EV traffic flow on the expressway remains relatively low. For example, during the Chinese Spring Festival (from 10 February to 17 February 2024), the average daily traffic of EVs on the expressway is 5.9392 million vehicles, only accounting for 10.04% of the average daily traffic (China Automotive News 2024). This could be attributed to the obvious gap between the rapid growth of BEVs' intercity travel demand and the configuration of charging infrastructures on the expressway network (Zhang et al. 2022). On one hand 21,000 charging piles have been launched in China's expressway service areas, which is relatively small compared with urban areas, where the number of charging piles has reached 6.631 million (CPIR 2024; Xin Hua Net 2024). The inadequate charging infrastructure network has led to an increase in BEV users' range anxiety on expressways (Zhang et al. 2022). On the other hand, there are some identified problems with the deployment, configuration, and service level of charging facilities launched in expressway service areas, including an uneven distribution of charging stations, a low charging power of charging piles, long queuing times, especially during holidays, high damage rate of charging piles and charging piles occupied by fuel vehicles (CBWP China Electric Vehicle User Charging Behavior White Paper 2022).

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The above issues not only downgrade the preference of existing BEV users to use charging infrastructures but also affect the willingness of potential users to purchase BEVs. For example, driving BEVs for long-distance expressway travel is difficult due to incomplete charging infrastructures and configurations, which hinders the willingness of traditional fuel vehicle users to purchase BEVs (Sonja and Anders Fjendbo, 2018). In addition, some consumers are reluctant to buy BEVs possibly because there are fewer charging facilities on the expressway, causing people to spend a lot of time queuing for an empty charging pile (Li et al. 2017; Solvi Hoen et al. 2023). Therefore, strengthening the construction of charging facilities on the expressway will help relieve BEV users' range anxiety, improve charging efficiency, further reduce users' charging and queuing time, increase BEV users' expressway travel satisfaction, and attract potential consumers with expressway travel needs to purchase BEVs (Fang et al. 2020; Pevec et al. 2020; Wang, Ke, and Zhao 2018). However, it is not completely clear to what extent do users react and perceive toward the existing charging infrastructures.

A better understanding of the factors influencing users' intentions to charge in expressway service areas is of utmost importance for the deployment of charging infrastructures and the improvement of service quality of charging infrastructures in the service area (Potoglou, Song, and Santos 2023; Wang, Yao, and Pan 2021). However, previous literature that focused on EV users' charging behavioral choices, preference for public charging infrastructures, charging satisfaction, and charging station' location selection, is mainly limited to urban areas. Few researchers have considered EV users' charging on the expressway, and none of the studies examine EV users' reuse intention after they have already used charging infrastructures launched on the expressway. The reasons why this study focuses on reusing intention toward charging infrastructures are as follows: Firstly, BEV users who have not used expressway charging infrastructures cannot evaluate the advantages and disadvantages that arise during the charging process. Therefore, the study population is the BEV owners who had recently used the charging infrastructures on the expressway, asking them to recall their perceptions when using charging infrastructures. Secondly, consumers would reevaluate their initial decisions after adopting certain services (Aw et al. 2019), and initial service experience will affect subsequent use (Weng et al. 2017). Thus, studying BEV users' reuse intention will help understand their perception and reaction toward charging infrastructures, thereby improving service quality in a targeted manner. In addition, this research concentrates on BEV users rather than PHEV users, as PHEV users can supplement their range by refueling in the service area (Ge, MacKenzie, and Keith 2018), so they do not have a strong need for charging in expressway service areas like BEV users. Therefore, it is necessary to analyze the BEV users' reuse intention toward charging infrastructures launched on the expressway service area, which is critical for charging infrastructures planning and operation.

Given the above, this current study focused on BEV users who had charged on the expressway and conducted a survey that explores their reuse intention toward charging infrastructures. Specifically, the main contributions are four aspects:

(1) Previous research scenarios focusing on BEV are mainly within urban areas. However, this article concentrates on BEV users' charging behavior on the expressway, which provides a theoretical reference for subsequent researchers who study BEV users' expressway travel.
(2) Designing a special questionnaire based on BEV users' driving characteristics on the expressway and the theory of planned behavior (TPB) to investigate their reuse intention toward charging infrastructures launched on the expressway.
(3) Revealing how psychological factors influence BEV users' reuse intention toward charging infrastructures using structural equation modeling and exploring heterogeneity across different BEV user groups in the effect of psychological factors on reuse intention using multi-group analysis.
(4) Providing implications to make better charging facility planning and marketing strategies, which could help increase the charging satisfaction of BEV users, thereby improving their expressway travel willingness and accelerating the completion of road decarburization goals.

Subsequent parts of this research are presented as follows: Section 2 briefly reviews the various attributes that influence EV users' charging choice behavior. In Section 3, the questionnaire design as well as data collection were presented, meanwhile, introducing the hypotheses development and research methodology. Section 4 presents the results of the measurement model, structural model, and multi-group analysis and discusses the research findings. Section 5 derives policy implications according to research findings and summarizes the conclusions and suggestions for future research.

2. Literature review

Previous research has explored various attributes that influence EV users' charging behavior, preference for public charging infrastructures, and EV adoption, including vehicle attributes, temporal attributes, charging infrastructure attributes, individual attributes, and psychological factors. This research aims to analyze what makes BEV users reuse charging infrastructures sited in expressway service areas, so a brief review that focuses on the above different types of influencing factors is provided below.

2.1. Vehicle attributes

Previous studies asserted that the inadequate battery status of EVs could lead to users' range anxiety, which drove their charging behavior (Pan, Yao, and MacKenzie 2019; Wen, MacKenzie, and Keith 2016; Xu et al. 2017). The battery status is usually represented as the current State of Charge (SOC), the remaining range, and the excess range (the difference between the range at the current SOC and the distance to the destination) (Potoglou, Song, and Santos 2023). Specifically, Wang, Yao, and Pan (2021) obtained the charging preference choices of 300 EV users in Beijing China and found that the remaining

SOC had a significant negative influence on charging behavior through the Binary logit (BL) model. Wen, MacKenzie, and Keith (2016) developed a mixed logit choice model to analyze BEV users' charging behaviors and indicated that excess range to home negatively influenced their charging choices for urban electric vehicle supply equipment. Besides, the performance of EVs including the driving range, battery capacity, and purchase cost also are the determinants of EV uptake (Mukherjee and Ryan 2020). Specifically, Hackbarth and Madlener (2016) employed a latent class model and analyzed the willingness to pay for EVs. Results showed that the driving range of EVs was found to be one of the major barriers to limiting consumer adoption. In addition, a high battery capacity would increase EV adoption slightly (Adepetu and Keshav 2017). Bjerkan, Nørbech, and Nordtømme (2016) investigated 3400 BEV owners to explore what incentives are critical for deciding to buy a BEV and found that purchase cost reduction is the strongest incentive in promoting BEV adoption.

2.2. Temporal attributes

The temporal attributes refer to charging time, queuing time, and time of day. Specifically, Yang et al. (2016) explored BEV users' route choice behavior in city areas based on the nested logit model, results indicated that users tended to choose routes that take less time to charge. Ge and MacKenzie (2022) developed a dynamic discrete choice model to study BEV users' charging behavior on long-distance travel. Results revealed that charging time and detour time significantly negatively correlated with users' charging choices. The queuing time refers to the time a user waits for a free charging pile at a charging station. Solvi Hoen et al. (2023) analyzed charging choice behavior on the long-distance trip of 465 respondents from a stated preference survey in Norway through a mixed logit model. Results showed that users were willing to pay €30 per hour to reduce queue time. Wang, Yao, and Pan (2021) divided the sample into two groups through the latent class logit model and found that queuing time reduced young users' willingness to charge. For the time of day, EV users usually use private charging piles to charge at night (Sun et al. 2018), which may be because nighttime is a low point on the power grid and therefore charging is inexpensive. During the daytime, when the power grid is at peak load hours, people tend to use public fast charging piles to charge their EVs (Ma, Yi, and Fan 2022; Moon et al. 2018), which suggests that EV drivers may combine charging with their daily travel activities, considering the trade-off between charging time and charging price.

2.3. Charging infrastructure attributes

Visaria et al. (2022) explored EV users' charging decisions and analyzed stated-choice experiment data of EV users based on a mixed logit model with random effects maximization. According to the modeling results, EV users are willing to detour an extra 0.28 mins to charge at a faster charging facility. Moreover, Wen, MacKenzie, and Keith (2016) also found that plug-in electric vehicle (PEV) owners would give priority to charging at the charging station with the greatest (50 KW) and second-highest (6.6 KW) charging power over charging at the lowest (1.9 KW) charging power. Ma, Yi, and Fan (2022) designed a discrete choice experiment to explore consumers' charging behavior, and results showed that fast charging was preferred by potential customers over slow charging. Regarding charging costs, people prefer to charge at cheap charging infrastructure (Daina, Sivakumar, and Polak 2017; Wang, Yao, and Pan 2021). Ge, MacKenzie, and Keith (2018) examined charging choices of PHEV drivers. Results indicated that those drivers who valued refueling costs more than charging costs were more likely to charge at a charging station. Accessibility to charging infrastructures also was confirmed as an important factor for EV users' charging behavior. For example, users were more likely to use public charging when the distance between the charging station and home/workplace/requested locations was shorter (Ma, Yi, and Fan 2022). Meanwhile, shorter detours were preferred by EV users when they employed en-route charging (Sun, Yamamoto, and Morikawa 2016). In addition, the infrastructures around the charging station such as supermarkets, toilets, and restaurants, can have a positive impact on EV users' preference for this charging facility (Ge and MacKenzie 2022; ten Have, Gkiotsalitis, and Geurs 2020; Visaria et al. 2022). Potoglou, Song, and Santos (2023) reported that the convenient functions within Charging infrastructures could improve the user's charging experience and they were very popular with EV users. For example, Wolff and Madlener (2019) found that EV users would rather pay an extra £7.40/month to use "inductive charging" (the driver can automatically charge the EV by simply driving it to a designated position) than traditional wired charging. Gutjar and Kowald (2023) found that EV users regarded the "plug and charge" (automatic authentication and payment) as the most convenient approach to charge. Instead of automatic debit transfers, potential EV customers choose payment options such as online and card-based (like credit cards) (Gutjar and Kowald 2023).

2.4. Individual attributes

For the individual attributes factor, different EV users may have different intentions to charge when faced with the same situation. Specifically, Wang, Yao, and Pan (2021) reported that EV users who liked to use public charging infrastructures tended to be young, female users, and experienced driving users. Zhang, Wang, and Lu (2022) explored BEV drivers' charging choice through a bivariate probit model. Results indicated that users with home charging piles were also less likely to charge at public charging infrastructures. ten Have, Gkiotsalitis, and Geurs (2020) used a mixed logit model with random effects maximization to analyze stated choice data of EV drivers. Results indicated that EV users with low income would prefer to use public charging infrastructures, besides, users with higher education would be more interested in super-fast charging. Similarly, Pan, Yao, and MacKenzie (2019) found that EV users with high educational levels are also inclined to use public charging infrastructures. Lee et al. (2020) surveyed 7,979 PEV owners and allowed them to respond with their historical charging behaviors over seven days. They found that those BEV users who owned a detached house were less likely to charge at public charging stations, and as the use age of EVs increased, PHEV users were more inclined to choose public charging stations. Yang et al. (2016) reported that EV users who worked in foreign companies or private companies, and freelancers were willing to take the risk of not charging their EVs. Since users in the above occupations have extremely high time value, they would rather risk running out of EV battery than spend time recharging them (Yang et al. 2016).

2.5. Psychological factors

Psychological factors also influence EV users' charging behavior and EV adoption. When considering individual risk attitude, Latinopoulos, Sivakumar, and Polak (2017) found that the decision about whether or not to charge an EV in a public charging station was impacted by risk-averse attitude regarding dynamic pricing. Pan, Yao, and MacKenzie (2019) categorized EV users based on risk attitude, and analyzed the charging behavior of each type of user separately, and found that users with a high-risk attitude to the EV range preferred to charge. In terms of range anxiety, it means that due to the limited cruising range, users will worry about the EV's battery being exhausted while driving (Zhang et al. 2021). The stronger the user's perception of range anxiety, the more likely they are to charge their EV (Wang, Yao, and Pan 2021; Wen, MacKenzie, and Keith 2016). Besides, several studies have pointed out range anxiety to be one of the major barriers to EV adoption (Melliger, van Vliet, and Liimatainen 2018; Skippon et al. 2016). Specifically, Skippon et al. (2016) studied how a driver's experience influences BEV adoption, and suggested that drivers are not willing to proceed with the BEV option once they experience the same due to its short range. In addition, many studies pointed out psychological aspects (e.g., moral values, emotion, environmental awareness) as significant determinants of EV adoption (He, Zhan, and Hu 2018; Schuitema et al. 2013; Smith et al. 2017). Specifically, consumer emotions and feelings influence attitudes and intentions to adopt EVs (Schuitema et al. 2013). Further, He, Zhan, and Hu (2018) found that personal innovativeness is one of the fundamental personality traits that influence EV adoption. Smith et al. (2017) studied the environmental enthusiast bias and found that traders holding higher environmental awareness had higher adoption intentions for EVs.

2.6. Research gaps

The aforementioned studies have mainly focused on the charging infrastructures of EVs within urban areas, with limited attention to those situated in expressway service areas, which help reduce electric vehicle users' range anxiety for expressway long-distance trips. In addition, little research has examined the effects of psychological factors on BEV users' reuse intention toward charging infrastructures on expressways. As a result, studies linking underlying psychological factors to BEV users' reuse intention toward charging infrastructures are lacking, especially in the context of expressways. The present study uses the theory of planned behavior (TPB) as a basis and combines it with perceived risk to understand the reuse intention of BEV users who have already charged in expressway service areas. Meanwhile, multi-group analysis is used to explore the heterogeneity across groups in the effect of psychological factors on BEV users' reuse intention.

3. Methodology

This section introduces the definitions of psychological latent variables that influence BEV users' reuse intention and the hypothesized relationships between them. Besides, the questionnaire design, as well as data collection, are presented, and then research methods (Structural Equation Model and Multi-group analysis) are briefly illustrated as follows.

3.1. Hypotheses and latent variables

Proposed by Ajzen (1991), the theory of planned behavior (TPB) which is commonly utilized to study individual behavior intention claims that an individual's intention to implement a certain action is predicted by their attitude (AT), subjective norm (SN), and perceived behavioral control (PBC).

Attitude (AT) is the user's evaluation of a particular behavior based on personal feelings and experiences (Buranelli de Oliveira et al. 2022). In this study, AT refers to how BEV users perceive the behavior of charging in expressway service areas. Some relevant studies also found AT to be a significant predictor of behavioral intention (Adu-Gyamfi et al. 2022; He et al. 2023). When an individual has a positive AT toward a particular behavior, their intention for this behavior is also higher (Knauder and Koschmieder 2019). Thus, BEV users may generate an intention to reuse the charging infrastructures when they find it advantageous to charge within the service area. Therefore, it is proposed that:

Hypothesis 1: Attitude significantly directly affects the reuse intention of BEV users toward charging infrastructures of the service area.

Subjective norm (SN) refers to the influence of important individuals or social pressures on an individual's behavior (Ajzen 1991). This external pressure may come from family, friends, mass media, and other reference objects (Adu-Gyamfi et al. 2022). Existing literature has shown that the greater the influence of external pressure, the greater the likelihood of forming an intention to engage in the behavior (Simsekoglu and Nayum 2019; Zhang and Li 2020). Thus, when relatives and friends or news media are more favorable to charging in the service area, or who all feel that charging infrastructures of the service area are important for BEVs running on the expressway, there is a subtle pressure on the BEV users to charge on the service area again. Therefore, we propose the following hypothesis in this paper:

Hypothesis 2: Subjective Norm significantly directly affects the reuse intention of BEV users toward charging infrastructures of the service area.

Perceived behavioral control refers to an individual's perception of how easy or difficult it is for him or her to perform a behavior (Ajzen 1991). Elnadi and Gheith (2022), Wang, Ke, and Zhao (2018), and Zhang and Li (2020) have demonstrated the importance of PBC for individuals to form behavioral intentions. As a result, BEV users are more likely to reuse charging infrastructures when they have the appropriate information and resources and feel that charging can be easily accomplished within the service area or have no concerns about charging in the service area. Accordingly, it is proposed that:

Hypothesis 3: Perceived behavioral control significantly directly affects the reuse intention of BEV users toward charging infrastructures of service areas.

The structure of the TPB can be modified (Cudjoe, Yuan, and Han 2020) to analyze individual intention toward certain behaviors from different aspects. Bamberg, Ajzen, and Schmidt (2003) argued that additional variables could be incorporated to improve the explanatory and predictive power of TPB. Many studies have emphasized the importance of taking an individual's risk perception into account when assessing their intention or reuse intention to engage in a behavior (Adu-Gyamfi et al. 2022; Nguyen, Nguyen-Phuoc, and Johnson 2023; Wang, Ke, and Zhao 2018; Y. Zhang et al. 2023). Therefore, this study integrates perceived risk (PR) into TPB.

As stated by Wang et al. (2020), PR refers to unforeseen consequences encountered by the users in the course of using the product or service, it may be financial, product performance, social, psychological, physical, or time risk. Thus, the greater the perceived risk is considered, the less likely users will accept a certain behavior (Jaiswal et al. 2021). Besides, PR may influence consumers' decision-making process (Elnadi and Gheith 2022). Previous studies have also demonstrated that users' perceived risk negatively affected their behavioral intentions (Han, Chua, and Hyun 2020; Y. Wang, Ke, and Zhao 2018; Zhang et al. 2023). Meanwhile, according to Adu-Gyamfi et al. (2022), the PR of consumer toward the battery swap technology greatly affects their attitudes and adoption of the technology. Elnadi and Gheith (2022) also found that PR affected users' attitudes toward using ride-hailing services. By studying the intention of micro-mobility vehicle users to charge illegally, Zhang et al. (2023) found that as users' PR decreased, their PBC and SN for the behavior of charging illegally would increase. Based on these findings, we propose the following hypotheses in this paper:

Hypothesis 4: Perceived risk significantly directly affects the Attitude (AT).

Hypothesis 5: Perceived risk significantly directly affects the Subjective norm (SN).

Hypothesis 6: Perceived risk significantly directly affects the Perceived behavioral control (PBC).

Hypothesis 7: Perceived risk significantly directly affects the reuse intention of BEV users toward charging infrastructures of the service area.

Previous studies have shown that the involvement of socio-demographic information and travel characteristics of individuals have a substantial impact on the execution of a certain behavior (Elnadi and Gheith 2022; Nguyen, Nguyen-Phuoc, and Johnson 2023; Si et al. 2022; Y. Zhang et al. 2023). Thus, BEV users of different ages, genders, incomes, driving ages, remaining SOC, and expressway traveling frequencies may have various impressions and understandings toward the charging infrastructures of the service area, finally resulting in different behavioral intentions. Therefore, this study hypothesizes that the relationship between latent variables is moderated by socio-demographic information and travel characteristics. Through recognizing the moderating role of these variables, this study seeks to advance understanding of the potential psychological differences when different BEV users are once again faced with charging options in the expressway service area. Based on the above hypothesis development, the integrated theoretical model of this research is depicted in Figure 1, which includes proposed moderating effects (blue section).

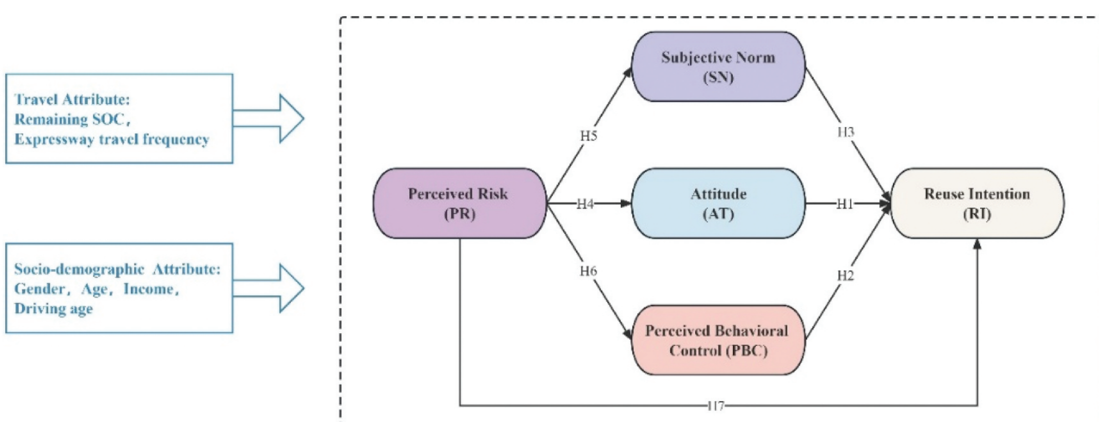


Figure 1. Integrated theoretical framework.

3.2. Survey design and data collection

This study aimed to understand BEV users' reuse intention toward charging infrastructures deployed in expressway service areas, especially understanding psychological factors that influenced them to reuse charging infrastructures. Similar to the study of Elnadi and Gheith (2022), they focused on existing ride-hailing service consumers and examined their intention to reuse the ride-hailing service, an online survey was conducted focusing on the BEV users who had already charged on the expressway. The survey consisted of three parts. The first part collected socio-demographic information including gender, age, annual income level, and driving age. In addition, respondents' expressway traveling attributes were also investigated, including the expressway traveling frequency and the BEVs' remaining SOC before departure (remaining SOC). The third part set the psychological latent variables (section 3.1) to capture the factors that influenced the reuse intention of BEV users toward charging infrastructures. The specific items for each latent variable are presented in Table 1. Well-established questionnaire scales from relevant studies were referenced in the questionnaire design process. Items were scored on a 5-point Likert scale from "completely disagree" (value = 1) to "completely agree" (value = 5) (Tang et al. 2021).

$$X = \Lambda_x \xi + \delta \tag{1}$$

The expression of endogenous latent variables is as follows:

$$Y = \Lambda_y \eta + \varepsilon \tag{2}$$

Λ_x and Λ_y are the factor loading matrix corresponding to endogenous latent variables ξ and exogenous latent variables η respectively. The explanations of other signs seen the Figure 2.

The Structural/Path Model is constructed by path analysis (He et al. 2023), in which the objective is to estimate the relationship between reuse intention and other psychological latent variables. The relationship between the path coefficients demonstrates the relationship between the various psychological latent variables, while the value of the path coefficients represents the degree of influence between the variables (Ding et al. 2023). The formula for the structural model is as follows:

$$\eta = B\eta + \Gamma\xi + \varphi \tag{3}$$

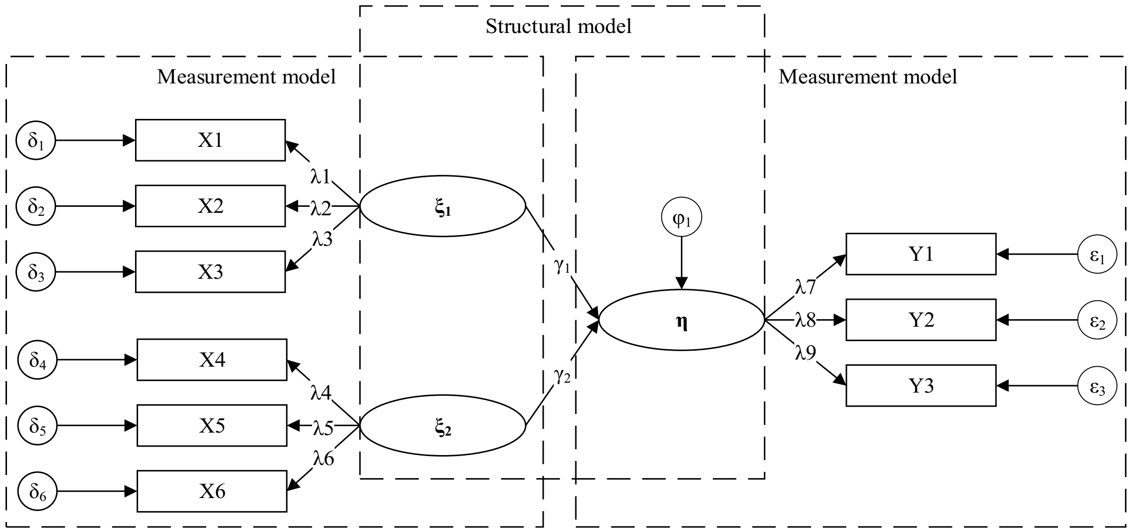
B and Γ are the regression coefficient matrices corresponding to endogenous latent variables ξ and exogenous latent variables η respectively. The explanations of other signs seen the Figure 2.

Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE) are used to examine the reliability and validity of the measurement model. The threshold is that Cronbach's alpha and CR are higher than 0.7, and AVE is higher than 0.5 (Anderson and Gerbing 1988; Chien et al. 2017; Hair et al. 2012; Xu et al. 2017). The Goodness of fit of the structural equation models was evaluated using the following indicators: the ratio of Chi-square to the degree of freedom (CMI/df), Normed fit index (NFI), Tucker-Lewis index (TLI), Comparative fit index (CFI), Incremental fit index (IFI), and Root mean square error of approximation (RMSEA) (Brown 2015; Hair et al. 2012; Satiennam et al. 2018). The threshold ranges of the above indicators are shown in Table 2

This study collected data through the Questionnaire Star sample service platform, completed from September 1, 2023, to September 18, 2023. A total of 486 BEV users participated in this survey. We obtained 376 valid questionnaires after filtering out incomplete cases with missing and extreme data (e.g., questionnaires with all options

Table 1. Latent and observed variables.

Latent variable	Items (18 in total)	References
Attitude(AT)	AT1 Charging in expressway service areas can ease my range anxiety. AT2 Charging in expressway service areas increases my expected travel distance. AT3 Charging infrastructures in expressway service areas provide stable energy support for my BEV. AT4 Charging in an expressway service area helps me reach my destination easily.	(Adu-Gyamfi et al. 2022; Du, Zhu, and Zheng 2021; Madigan et al. 2017)
Subjective Norm (SN)	SN1 News media have positively influenced my choice to charge in expressway service areas. SN2 My relatives and friends recommend I charge in expressway service areas. SN3 Friends and family who have charged their electric vehicles in expressway service areas have given them good reviews.	(Buranelli de Oliveira et al. 2022; He et al. 2023)
Perceived Behavioral Control (PBC)	PBC1 The procedure of charging in expressway service areas is not complicated for me. PBC2 I'm pretty sure I'll be able to charge it in the expressway service area without any problems. PBC3 I can solve some common problems when charging in expressway service areas. PBC4 It's easy for me to find service areas for charging on the expressway	(Y. Zhang and Li 2020; Zhang et al. 2023)
Perceived Risk (PR)	PR1 Worried that the charging process will take too long and delay my subsequent trip planning. PR2 Worried about the charging power of the charging infrastructures in the service area does not match my BEV. PR3 Worried about the sudden failure of charging piles in expressway service areas. PR4 Worried about my personal information being leaked when I registered for the charge application program (APP). PR5 Worried about high charging costs and payment information being stolen.	(Adu-Gyamfi et al. 2022; Elnadi and Gheith 2022)
Reuse Intention (RI)	RI1 I would be willing to charge my BEV at the service area on my future expressway travel. RI2 I would recommend my relatives and friends to charge their BEVs in expressway service areas.	(Adu-Gyamfi et al. 2022; Lee, Kim, and Roh 2023)



Legend:
ξ — Exogenous latent variable
η — Endogenous latent variable
X — Observed variable of exogenous latent variable
Y — Observed variable of endogenous latent variable
δ， φ and ε — Error coefficients for x, η and Y
λ — Factor loading
γ — Regression coefficient (path coefficient)

Figure 2. The structure of SEM.

chosen to be the same). The sample size of this study is greater than 300 and not less than 15 times the number of variables ($15 \times 18 = 270$), satisfying the statistical requirements (Jaiswal et al. 2021).

3.3. Structural equation model

Structural equation modeling (SEM) is a multivariate data analysis methodology to analyze the relationship between variables based on their covariance matrix (Byrne 2013). This method combines factor analysis, multiple correlation, regression, and path analysis, which can avoid excessive multi-collinearity compared with multiple regression analysis (Xiong et al. 2014). In addition, Structural equation modeling (SEM) has been wildly used to explore the relationships between consumers' usage intentions and psychological latent variables (Buranelli de Oliveira et al. 2022; Elnadi and Gheith 2022; Neto et al. 2020). Similarly, this article employed the SEM to analyze BEV users' reuse intention toward charging infrastructures. The SEM is split into the Measurement model and the Structural/Path Model (Byrne 2013), as shown in Figure 2.

The Measurement Model is constructed by Confirmatory Factor Analysis (CFA), in which its validity and reliability are verified from the relationship between the latent variables and their observed variables (Buranelli de Oliveira et al. 2022). In this study, latent variables are psychological variables such as attitudes, subjective norms, perceived behavioral control, and perceived risk, which cannot be measured directly. Specifically, it can be divided into endogenous latent variables and exogenous latent

Table 2. Evaluation index and standard of fit degree of SEM.

Evaluation indicators	Recommended threshold	Reference
CMI/df	Between 1 and 3	(Cheung and Rensvold 2002; Hu and Bentler 1999)
RMSEA	<0.08	
NFI	>0.9	
TLI	>0.9	
IFI	>0.9	
CFI	>0.9	

variables. Observed variables refer to the specific items corresponding to each latent variable, as shown in Table 1. In the measurement model, the expression of exogenous latent variables is as follows:

3.4. Multi-group analysis

The Multi-group analysis is usually used to understand whether the model behaves consistently across different groups (such as different genders, ages, and cultural backgrounds), or whether there are significant differences in model parameters (Nguyen, Nguyen-Phuoc, and Johnson 2023; Tiruwa, Yadav, and Suri 2018). For example, Si et al. (2022) used the MGA method to examine the differences in carpooling behavior intention by different genders, educational levels, and ages. Therefore, to capture the differences in the intention to reuse charging infrastructure among each group based on individuals' socio-demographic attributes and expressway traveling attributes, the multi-group analysis approach could provide beneficial help. The premise of this method is to identify the different groups that need to be compared. Referring to Jaiswal

Table 3. Reclassification groups ($N = 376$).

Variable	Category	Sample mean	Category	Frequency	Percentage (%)
Gender	Male = 1	1.32	Male	255	67.8
	Female = 2		Female	121	32.2
Age (years)	18–25 = 1	2.55	Younger (below 30)	149	39.6
	26–30 = 2				
	31–40 = 3		Elder (over 30)	227	60.4
	41–50 = 4				
	50 and over = 5				
Annual income (CNY) (1 USD = 7.32 CNY (accessed 2 November 2023)	Below 8,0000 = 1	2.10	Low income	275	73.1
	80,000–160,000 = 2				
	Over 160,000 = 3		High income	101	26.9
Driving age (years)	Below 1 = 1	3.40	Inexperienced	171	45.5
	1–3 = 2				
	4–6 = 3				
	7–10 = 4		experienced	205	54.5
	10 and over = 5				
Expressway traveling frequency	once every six months or less = 1	2.71	Low frequency	156	41.5
	once every three months = 2				
	once or twice a month = 3		High frequency	220	58.5
	once a week = 4				
	at least three times a week = 5				
Remaining SOC	90%–100% = 1	1.65	High SOC	203	54.0
	80%–90% = 2		Low SOC	173	46.0
	70%–80% = 3				
	60%–70% = 4				
	60% and under = 5				

et al. (2021), the mean of the sample is used to split into two groups. The sample mean is calculated by dividing the sum of the sample values by the sample size (376). For example, the age sample mean was 2.55, so the sample is divided into a younger group of less than 2.55 (under 30 years old), and an elder group of more than 2.55 (beyond 30 years old). The grouping result of the other variables is shown in Table 3.

The multi-group analysis includes two steps: examining model invariance and comparing the multi-group difference (He et al. 2023). The model invariance is performed to test whether the variables operated equivalently, which means whether the models of different groups are statistically identical (Bowen and Guo 2011). First, an initial model specifying identical structural and measurement equations for all groups generates estimates for each group and yields fit indices that are applied to the multi-group model. With new constraints added to the model, the goodness-of-fit indicators change, which is the standard way to assess the model invariance (He et al. 2023). In this research, determining whether the model is invariant using a chi-square (χ^2) difference test. When the test result for two adjacent models with different constraint levels is significant ($p < .05$), the model invariance is not recognized (Zhao and Gao 2022). For the restrictions, there are five levels of the invariance model, and the constraints at each level are created in a way consistent with the recommendations of Byrne (2013) and Kline (1998).

Variables that did not satisfy the model invariance test were used to compare multi-group differences (Elnadi and Gheith 2022; He et al. 2023; Si et al. 2022). Specifically, each group generated the corresponding path coefficients after the model invariance test. The P-value for the difference in path coefficients was used to determine whether the categorical variable has a moderating effect (Elnadi and Gheith 2022; Nguyen, Nguyen-Phuoc, and Johnson 2023).

4. Results

This section presents the research results. Specifically, section 4.1 introduces the socio-demographic profile of the study population. Section 4.2 analyzes the reliability and validity of the measurement model. Various hypothesized relationships between latent variables are verified in Section 4.3, and then discussing the results of the structural model. Section 4.4 presents the results of the multi-group analysis and discusses the heterogeneities among different BEV users.

4.1. Socio-demographic profile

Table 4 presents the demographic and travel characteristics of the respondents. It can be seen that more than two-thirds of the respondents are male, and almost 53% of the respondents are between 31 and 40 years of age. More than 50% of the respondents have an annual income level between 80,000 and 160,000. There are 42% of respondents who have been driving for between 5 and 10 years, besides, about 40% of respondents driving on the expressway once or twice a month. Approximately 86% of the total sample keep their BEVs at about 90% before pulling onto the expressway.

Table 5 presents the descriptive statistics of the observed indicators. Notably, all constructs exhibit absolute skewness

Table 4. Descriptive statistics of the sample ($N = 376$).

Variable	Category	Frequency	Percentage (%)
Gender	Male	255	67.8
	Female	121	32.2
Age (years)	18–25	57	15.2
	26–30	92	24.5
	31–40	199	52.9
	41–50	19	5.1
	50 and over	9	2.4
Annual income (CNY)	Below 8,0000	63	16.8
(1 USD = 7.32 CNY (accessed 2 November 2023)	80,000–160,000	212	56.4
	Over 160,000	101	26.9
Driving age (years)	Below 1	28	7.4
	1–3	46	12.2
	4–6	97	25.8
	7–10	158	42.0
	10 and over	47	12.5
Expressway traveling frequency	once every six months or less	46	12.2
	once every three months	110	29.3
	once or twice a month	143	38.0
	once a week	62	16.5
	at least three times a week	15	4·.0
Remaining SOC	90%–100%	203	54.0
	80%–90%	121	32.2
	70%–80%	38	10.1
	60%–70%	11	2.9
	60% and under	3	0.8

Table 5. Mean, standard deviation, skewness, and kurtosis ($N = 376$).

	Items	Mean	Standard deviation	Skewness	Kurtosis
AT	AT1	3.79	1.147	−0.964	0.191
	AT2	3.92	1.094	−1.137	0.767
	AT3	3.78	1.098	−1.005	0.404
	AT4	3.91	1.135	−1.197	0.777
SN	SN1	3.65	1.030	−0.243	−1.016
	SN2	3.70	1.033	−0.377	−0.821
	SN3	3.61	1.008	−0.214	−0.966
PBC	PBC1	3.69	1.222	−0.889	−0.157
	PBC2	3.98	1.209	−1.208	0.561
	PBC3	3.72	1.093	−1.023	0.505
	PBC4	3.57	1.171	−0.767	−0.188
	PBC5	3.39	1.032	−0.343	−0.538
PR	PR1	3.07	1.223	−0.076	−0.966
	PR2	3.22	1.239	−0.238	−1.049
	PR3	2.82	1.114	0.275	−0.746
	PR4	2.71	1.152	0.285	−0.746
	PR5	3.83	1.092	−1.042	0.566
RI	RI1	3.73	1.076	−1.004	0.590
	RI2	3.79	1.147	−0.964	0.191

and kurtosis values below 2 and 7, respectively, indicating that the data distribution conforms to normality assumptions and satisfies the maximum likelihood (ML) estimation requirements in SEM (Kline 2023).

4.2. Measurement model result

Table 6 demonstrates the reliability and validity of the measurement model. The Cronbach's alpha is greater than 0.7, which indicates good reliability of the questionnaire and good internal consistency in each latent variable (Anderson and Gerbing 1988; Chien et al. 2017). The CR of the latent variables are all above 0.7, which is a very satisfactory result. Thus, the measurement model has good construct reliability (Ding et al. 2023). All factor loadings (Standardized estimate) exceed the recommended threshold (0.6), which is a very satisfactory result (Hair 2009). The AVE of the "Subjective Norm" variable presents a value slightly below the ideal (0.490). However, its CR value is above the limitation (0.740), so it is considered to be satisfied and remains in the model. Similarly, the value of AVE of the "constraints" variable in Buranelli'study is 0.486 less than 0.5, but the variable is maintained because its CR (0.67) is satisfactory (Buranelli de Oliveira et al. 2022). The measurement model has sufficient convergent validity because the value of factor loading and AVE meets the requirement (Wang, Ke, and Zhao 2018).

As shown in Table 7, the square root of AVE (on the diagonal) for each latent variable is higher than its correlations with another latent variable, suggesting acceptable discriminant validity for the measurement model (Fornell and Larcker 1981).

Table 6. Composite reliability and convergent validity of the measures.

Latent variable	Indicator	Standardized estimate	Estimate	S.E.	T-value	P-value	CR	AVE	Cronbach's α
SN	SN1	0.662	1.000	—	—	P < 0.001	0.740	0.490	0.737
	SN2	0.799	1.211	0.127	9.503	P < 0.001			
	SN3	0.626	0.926	0.100	9.305	P < 0.001			
AT	AT1	0.853	1.000	—	—	P < 0.001	0.890	0.669	0.890
	AT2	0.813	0.910	0.05	18.162	P < 0.001			
	AT3	0.798	0.896	0.05	18.041	P < 0.001			
	AT4	0.806	0.935	0.052	17.848	P < 0.001			
PR	PR1	0.685	1.000	—	—	P < 0.001	0.862	0.557	0.862
	PR2	0.746	1.292	0.100	12.863	P < 0.001			
	PR3	0.690	1.210	0.101	11.978	P < 0.001			
	PR4	0.795	1.257	0.109	11.522	P < 0.001			
	PR5	0.803	1.310	0.113	11.565	P < 0.001			
PBC	PBC1	0.884	1.200	0.061	16.175	P < 0.001	0.889	0.668	0.888
	PBC2	0.801	1.076	0.067	16.022	P < 0.001			
	PBC3	0.810	0.983	0.061	0.061	P < 0.001			
	PBC4	0.769	1.000	—	—	P < 0.001			
RI	RI1	0.821	1.000	—	—	P < 0.001	0.767	0.622	0.766
	RI2	0.756	0.907	0.201	4.505	P < 0.001			

Note: Significant at: *$p < .05$, **$p < .01$ and ***P<0.001, "—" denote null value.

Table 7. Discriminant validity of latent variables.

	SN	AT	PR	RI	PBC
SN	**0.700**				
AT	0.240	**0.818**			
PR	−0.119	−0.110	**0.746**		
RI	0.199	0.237	−0.290	**0.789**	
PBC	0.244	0.291	−0.132	0.127	**0.817**

Note: Off-diagonal elements are correlations between constructs; Diagonal elements are the square root of the average variance extracted. ($N = 376$).

Figure 3 illustrates the result of confirmatory factor analysis (CFA). The values of the model fit indicators are CMI/df = 2.494, RMSEA = 0.063, CFI = 0.940, TLI = 0.927, and IFI = 0.941. The values of all fit indices satisfy the conditions (Table 2), which suggests that the measurement model is a good fit.

4.3. Structural model result

This study used structural equation modeling to analyze the relationship between the latent variables via Amos 28.0. The overall fit of the model is shown in Figure 4, CMI/df = 2.795 is between 1 and 3, RMSEA = 0.069 is less than 0.08, and CFI = 0.927, TLI = 0.912, and IFI = 0.927 are all greater than 0.9, which indicates that the structural model fits the observed data well.

Table 8 presents the results of path analysis. If the path coefficient is higher than 0.1, the T-value is higher than 1.96, and the P-value is less than 0.05, then the statistical significance of the hypothesis is accepted (Buranelli de Oliveira et al. 2022), so all hypotheses except H6 and H7 are statistically confirmed at significance levels of p-value less than 0.05 or 0.01. As illustrated in Table 8 and Figure 4, Attitude (AT) positively influences Reuse Intention (RI), confirming H1 ($\beta = 0.201$, T-value = 3.019, $p = .003$). Meanwhile, according to the descriptive analysis (Table 5), the participators regard charging in expressway service areas as a helpful, favorable, and positive attitude. This finding is in tandem with previous relevant studies (Adu-Gyamfi et al. 2022; Buranelli de Oliveira et al. 2022; Curtale, Liao, and van der Waerden 2021; Wang, Ke, and Zhao 2018), indicating that BEV users who believe that charging at expressway service areas can help accomplish their travel purposes more smoothly are more likely to reuse charging infrastructures.

Subjective Norm (SN) has a positive effect on Reuse Intention (RI), confirming H2. ($\beta = 0.145$, T-value = 2.005, $p = .045$). This finding aligns with previous research, indicating the importance of subjective norms as predictors of behavioral intentions (Nguyen, Nguyen-Phuoc, and Johnson 2023; Si et al. 2022; Zhang et al. 2023). Reference news media, family, and friends matter in the BEV users' decision-making process regarding whether to use charging infrastructures at expressway service areas. However, Perceived Behavioral Control (PBC) is statistically insignificant in affecting Reuse Intention (RI), disproving H3 ($\beta = 0.051$, T-value = 0.782 $p = .434$). This finding is similar to Adu-Gyamfi et al. (2022), which suggests that there is no significant relationship between consumers' perceived behavioral control and battery swap intention. The process of charging in expressway service areas is the same as in urban areas, and most BEV users are already familiar with the charging infrastructures and the charging process in their day-to-day life, so their reuse intention will not be impacted by the perceived behavioral control when BEV users are confident that they can complete charging on the expressway.

Perceived Risk (PR) negatively affects Perceived Behavioral Control (PBC) ($\beta = -0.140$, T-value = −2.377, $p = .017$), Subjective Norm (SN) ($\beta = -0.127$, T-value = −1.978, $p = .05$) and Attitude (AT) ($\beta = -0.119$, T-value = 2.013, $p = .044$), affirming H6, H5 and H4. The findings confirm that of Jaiswal et al. (2021), Featherman et al. (2021), and Zhang

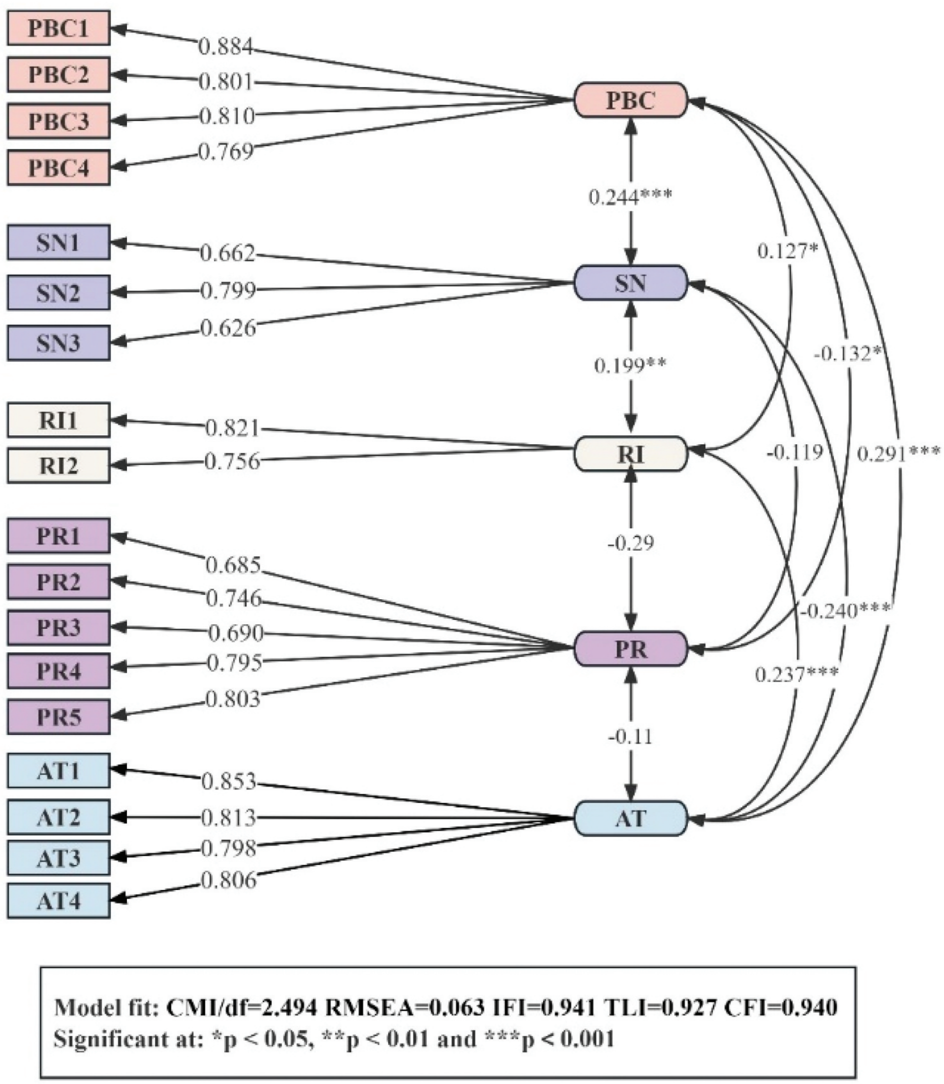


Figure 3. Confirmatory factor analysis results.

et al. (2023). Moreover, perceived risk (PR) does not have a significant direct effect on reuse intention (RI), disproving H7. (β = 0.017, T-value = 0.261 $p = .794$). This may be because charging infrastructures are limited in expressway service areas and are not as densely distributed as in urban areas (Globisch et al. 2019), so BEV users are reluctant to give up a rare charging opportunity, even if there is a certain amount of risk involved.

Table 9 shows the results of the indirect effect of perceived risk on reuse intention, which is conducted using Amos' bootstrap algorithm. The total indirect effect of Perceived Risk (PR) on Reuse Intention (RI) is −0.062, this further explains the mediating role of Attitudes (AT), Subjective Norms (SN), and Perceived Behavioral Control (PBC) between Perceived Risk (PR) and Reuse Intention (RI). The mediation effect is indirect-only mediation (full mediation) since the direct effect of Perceived Risk (PR) on Reuse Intentions (RI) is not significant. This result supports the findings of Adu-Gyamfi et al. (2022), Ding et al. (2023), and Zhang et al. (2023), who found that users with higher risk perception have more negative attitudes and weaker subjective norm.

4.4. Model invariance and multi-group analysis

Model invariance and multi-group analysis are performed to determine whether there is heterogeneity across BEV user groups. First, model invariance is tested on all socio-demographic and travel attributes respectively. Once the chi-square test is significant, the multi-group analysis is performed using AMOS software to analyze the difference between groups.

The results of the model invariance test are presented in Table 10. The $\Delta\chi^2$ difference test result between the unconstrained model and measurement weights model is significant ($p = .026$ and 0.038), meaning that model invariance does not hold among different age groups and driving age groups. The $\Delta\chi^2$ difference test result between the structural residuals model and measurement residuals model is significant

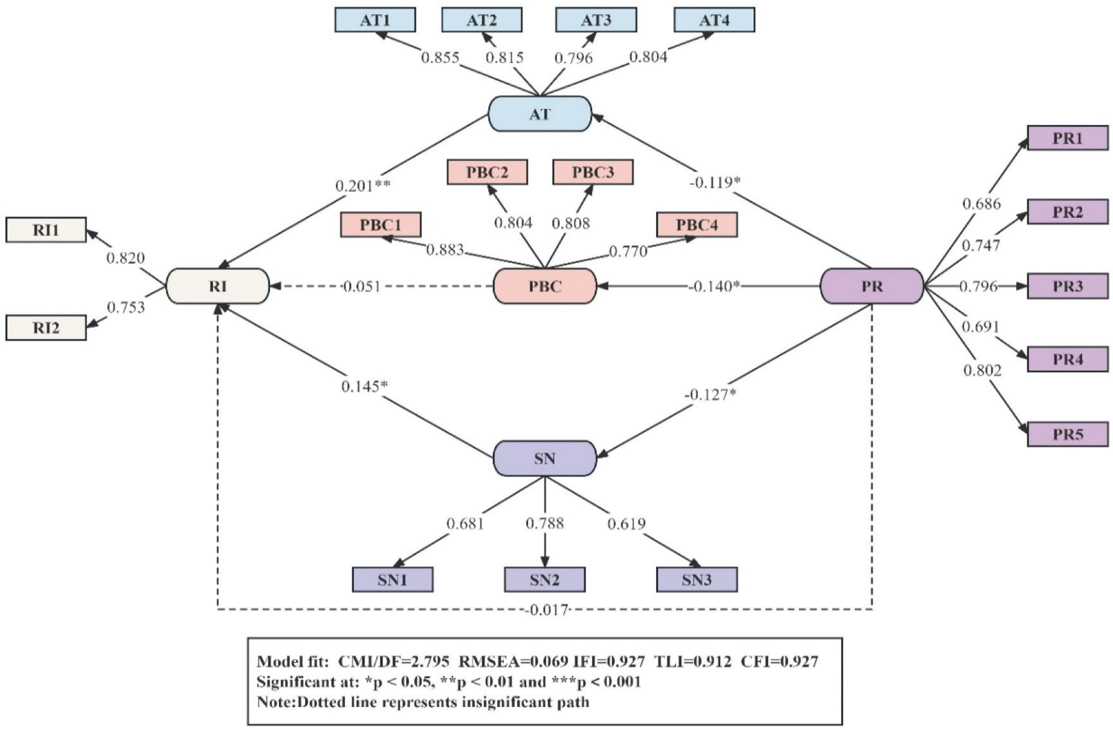


Figure 4. Graphical representation of hypotheses test results.

Table 8. Results of path analysis.

Hypothetical	Path	Estimate(β)	S.E.	T-Value	P-value	Result
H6	PR→PBC	−0.140	0.090	2.377	0.017*	Support
H5	PR→SN	−0.127	0.057	1.978	0.050*	Support
H4	PR→AT	−0.119	0.076	2.013	0.044*	Support
H1	AT→RI	0.201	0.065	3.019	0.003**	Support
H2	SN→RI	0.145	0.103	2.005	0.045*	Support
H3	PBC→RI	0.051	0.053	0.782	0.434	Not Support
H7	PR→RI	−0.017	0.083	0.261	0.794	Not Support

Note: Significant at: $^{*}p < .05$, $^{**}p < .01$.

Table 9. Mediating effects of psychological factors on RI.

Path	Standardized indirect impact	Coefficient	
PR→AT→RI	Coefficient (PR→AT)* Coefficient (AT→RI)	−0.030	
PR→SN→RI	Coefficient (PR→SN)* Coefficient (SN→RI)	−0.009	
PR→PBC→RI	Coefficient (PR→PBC)* Coefficient (PBC→RI)	−0.023	
Total indirect impact		**Bias-corrected 95% CI**	
		Lower	**Upper**
PR→RI	−0.062*	−0.119	−0.021

Note: 2000 bootstrap samples; 95% confidence interval; *p < 0.05.

(p = .006), indicating that model invariance is not recognized among different expressway traveling frequency groups. The $\Delta\chi^2$ difference test result between the structural covariances model and the structural residuals model is significant (p = .004), demonstrating that model invariance does not exist among different remaining SOC groups. Besides, model invariance is recognized among different gender and income groups, as the $\Delta\chi^2$ difference test result is not significant (p>0.05) across all models

As the model invariance test shows no significant differences across groups, including gender and income, further analysis is not made for those variables. Table 11 displays the results of the multi-group analysis including age, driving age, expressway travel frequency, and remaining SOC. It is suggested that if the P-value of the path coefficient difference is lower than 0.05, then the statistical significance of the moderating effect of the variable is accepted (Nguyen, Nguyen-Phuoc, and Johnson 2023). Specifically, on the Perceived Risk (PR) to Perceived Behavioral Control (PBC) (p = .014) and Attitude (AT) to Reuse Intention (RI) (p = .046) pathway, the remaining SOC is a significant moderating variable. Firstly, the effect of perceived risk (PR) on perceived behavioral control (PBC) is significant among users with high remaining SOC, while the impact among users with low remaining SOC is insignificant. This may be because BEV users with a high remaining SOC before departure have less range anxiety (Zhang et al. 2021), therefore they are better able to make rational choices. Secondly, the attitude (AT) has a significant positive impact on the reuse intention (RI) of respondents with low remaining SOC, while this impact on respondents with high remaining SOC is not significant. Users with lower

Table 10. Results of multi-group invariance test.

	χ^2	χ^2/df	RMSEA	CFI	Nested	$\Delta\chi^2$	$\Delta\chi^2$ difference test (p-value)
model	Gender						
Unconstrained(1)	486.914	1.902	0.049	0.926	—	—	—
Measurement weights(2)	501.102	1.863	0.048	0.926	(2) - (1)	14.188	0.361
Structural weights(3)	503.754	1.825	0.047	0.927	(3) - (2)	2.651	0.915
Structural covariances(4)	503.846	1.819	0.047	0.927	(4) - (3)	0.092	0.762
Structural residuals(5)	508.844	1.811	0.047	0.927	(5) - (4)	4.998	0.288
Measurement residuals(6)	525.341	1.757	0.045	0.927	(6) - (5)	16.498	0.558
model	Age						
Unconstrained(1)	489.282	1.911	0.049	0.925	—	—	—
Measurement weights(2)	513.917	1.910	0.049	0.922	(2) - (1)	24.635	**0.026**
Structural weights(3)	514.607	1.865	0.048	0.924	(3) - (2)	0.690	0.998
Structural covariances(4)	515.044	1.859	0.048	0.924	(4) - (3)	0.437	0.509
Structural residuals(5)	518.645	1.846	0.048	0.924	(5) - (4)	3.602	0.463
Measurement residuals(6)	542.088	1.813	0.047	0.922	(6) - (5)	23.443	0.174
model	Driving age						
Unconstrained(1)	493.576	1.928	0.050	0.924	—	—	—
Measurement weights(2)	516.890	1.922	0.050	0.921	(2) - (1)	23.314	**0.038**
Structural weights(3)	521.860	1.891	0.049	0.921	(3) - (2)	4.970	0.664
Structural covariances(4)	521.860	1.844	0.049	0.922	(4) - (3)	0.000	0.986
Structural residuals(5)	525.878	1.871	0.048	0.922	(5) - (4)	4.018	0.404
Measurement residuals(6)	538.388	1.801	0.046	0.923	(6) - (5)	12.510	0.820
model	Expressway traveling frequency						
Unconstrained(1)	511.951	2.000	0.052	0.919	—	—	—
Measurement weights(2)	528.637	1.965	0.051	0.917	(2) - (1)	16.686	0.214
Structural weights(3)	531.370	1.925	0.050	0.919	(3) - (2)	2.733	0.909
Structural covariances(4)	533.157	1.925	0.050	0.918	(4) - (3)	1.787	0.181
Structural residuals(5)	535.958	1.907	0.049	0.919	(5) - (4)	2.801	0.592
Measurement residuals(6)	572.537	1.915	0.049	0.913	(6) - (5)	36.579	**0.006**
model	Remaining SOC						
Unconstrained(1)	485.188	1.895	0.049	0.926	—	—	—
Measurement weights(2)	498.584	1.853	0.048	0.926	(2) - (1)	13.396	0.418
Structural weights(3)	504.625	1.828	0.047	0.926	(3) - (2)	6.040	0.535
Structural covariances(4)	504.660	1.822	0.047	0.926	(4) - (3)	0.035	0.852
Structural residuals(5)	519.822	1.850	0.048	0.923	(5) - (4)	15.162	**0.004**
Measurement residuals(6)	544.109	1.820	0.047	0.921	(6) - (5)	24.287	0.146
model	Income						
Unconstrained(1)	525.233	2.052	0.915	0.053	—	—	—
Measurement weights(2)	543.344	2.020	0.913	0.052	(2) - (1)	18.110	0.153
Structural weights(3)	546.252	1.979	0.914	0.051	(3) - (2)	2.908	0.893
Structural covariances(4)	546.258	1.972	0.915	0.051	(4) - (3)	0.006	0.939
Structural residuals(5)	554.758	1.974	0.913	0.051	(5) - (4)	8.501	0.075
Measurement residuals(6)	578.845	1.936	0.911	0.050	(6) - (5)	24.087	0.152

Note:"—" denote the null value.

Table 11. Multi-group analysis results.

		PR→PBC	PR→SN	PR→AT	PR→RI	AT→RI	SN→RI	PR→RI
Age (years)	younger	−0.159	−0.077	−0.113	0.106	0.028	0.095	−0.019
	elder	−0.128	−0.147	−0.115	0.025	0.279*	0.173	−0.013
	Δβ	0.031	0.07	0.002	−0.081	0.251	0.078	0.006
	P-value for Δβ	0.589	0.682	0.768	0.587	**0.011**	0.938	0.893
Driving age (years)	Inexperienced	−0.17*	−0.185	−0.104	0.002	0.283*	0.050	−0.049
	experienced	−0.092	−0.112	−0.118	0.084	0.119	0.236*	−0.019
	Δβ	0.078	0.073	0.014	0.082	0.164	0.186	0.03
	P-value for Δβ	0.376	0.484	0.981	0.415	0.537	**0.048**	0.610
Expressway traveling frequency	Low	−0.157	−0.178	−0.102	0.116	0.072	0.229*	−0.038
	High	−0.143	−0.092	−0.125	0.112	0.181*	0.014	−0.041
	Δβ	0.014	0.086	0.023	0.004	0.109	0.215	0.003
	P-value for Δβ	0.503	0.228	0.729	0.384	**0.009**	**0.040**	0.786
Remaining SOC	Low	−0.034	−0.172*	−0.119	0.015	0.305**	0.130	−0.056
	High	−0.234*	−0.133	−0.151	0.106	0.076	0.122	0.054
	Δβ	0.200	0.039	0.032	0.091	0.229	0.008	0.110
	P-value for Δβ	**0.014**	1.392	1.328	0.390	**0.046**	0.978	0.410

Note: Significant at: *$p < .05$, **$p < .01$. Δβ: Path coefficient difference.

remaining SOC before departure will have a greater need for charging infrastructures. Previous studies showed users' decisions to use public charging are negatively associated with remaining SOC (Pan, Yao, and MacKenzie 2019; Wen, MacKenzie, and Keith 2016; Xu et al. 2017). Therefore, this group is more likely to have a positive attitude and have a higher intention to reuse charging infrastructures of expressway service areas.

Expressway traveling frequency is a significant moderating variable on the Attitude (AT) to Reuse Intention (RI) ($p = .009$)

and Subjective Norm (SN) to Reuse Intention (RI) (p = .040) paths. Firstly, the attitude (AT) of frequent expressway travelers has a significant positive impact on their reuse intention (RI), while for respondents with low traveling frequencies, this path is not significant. This may be because users who travel more frequently are more familiar with the advantages of charging infrastructures of service areas. This view is similar to ten Have, Gkiotsalitis, and Geurs (2020), which indicates that EV users who have a higher usage frequency of fast charging tend to select fast charging when they have charging needs. Secondly, the subjective norm (SN) has a significant positive impact on the reuse intention (RI) of respondents with low traveling frequencies, while this impact on frequent traveling respondents is not significant. This may be because BEV users with less frequent expressway trips are more likely to ask others about their charging experiences and are more susceptible to external influences and thus have a higher intention to reuse charging infrastructures of the service area.

Driving age is a significant moderating variable on the Subjective Norm (SN) to Reuse Intention (RI) (p = .048) pathway. Specifically, the subjective norm (SN) has a positive effect on the reuse intention (RI) of experienced drivers, while its impact on inexperienced drivers is not significant. As driving experience increases, drivers become more sensitive to their surroundings, therefore they will be more likely to be socially influenced (Xu, Li, and Jiang 2014), and may consider the opinions of those around them more when making adoption and usage decisions. Besides, age is a significant moderating variable on the Attitude (AT) to Reuse Intention (RI) (p = .011) confirming the findings of Tiruwa, Yadav, and Suri (2018), which age of consumers moderates the effect of attitude on purchase intentions of online brand communities. Specifically, the positive effect of attitude (AT) on reuse intention (RI) is significant in elderly BEV users (beyond 30 years), while this impact on younger BEV users (under 30 years old) is not significant. This is reasonable because elderly people have rich social experiences (Si et al. 2022), therefore they will be more likely to have a positive attitude toward charging infrastructures on the expressway.

5. Conclusions and recommendations

This section first generalizes the main research findings of this study. Next, policies are proposed in terms of improving BEV users' attitudes toward charging infrastructures launched in the expressway service area. Finally, limitations and recommendations for future research are proposed in 5.3.

6. Conclusions

This study holds significant importance for the following reasons: 1) Theoretical significance: this research validates the applicability of the Theory of planned behavior (TPB) in explaining and predicting BEV users' charging behavior on the expressway, and extends the application of the TPB. In addition, a novel framework with more explanatory power is developed by considering the external intervention variables: perceived risk, which provides a foundation for future research on BEV users' expressway travel. 2) Practical significance: This study analyzed BEV users' reuse intention toward charging infrastructures, providing useful implications to make better charging infrastructure planning and marketing strategies. This helps drive EV adoption, enabling sustainable development and accelerating road decarburization targets.

Results show that attitude and subjective norm positively influence the reuse intention. However, BEV users' perceived behavioral control is insignificant to the reuse intention. Secondly, perceived risk negatively influences attitude, subjective norm, and perceived behavioral control significantly. Meanwhile, perceived risk has an indirect negative effect on reuse intention mediated by attitudes, subjective norms, and perceived behavioral control. Third, the multi-group analysis reveals differences in perceptions and understandings of the behavior that reuse charging infrastructures launched on expressways among BEV users with different ages, driving ages, remaining SOC, and expressway traveling frequencies. Specifically, the attitude has a more significant effect on reuse intention among users beyond 30 years old, high-frequency users, and low remaining State of Charge (SOC) users. Besides, the subjective norm has a more significant effect on reuse intention among experienced drivers and low-frequency users.

6.1. Policy implications

The research findings provide several critical implications for governments and charging infrastructure operators to drive the construction and use of charging facilities on the expressway, which is significant to achieving carbon emission reduction targets for road transport. The main implications are given as follows:

It is obvious that attitude significantly influences reuse intention toward charging infrastructures positively. Thus, improving BEV users' attitudes toward charging infrastructures launched in service areas can help attract more users. Firstly, the improvement and convenience of charging infrastructures in expressway service areas should be promoted through advertising, social media, and other channels to increase BEV users' trust and recognition. Secondly, The Fast-charging piles should be developed by making significant investments to improve charging efficiency and the coverage density of charging infrastructures on the expressway should be expanded. For instance, charging infrastructures should be covered at important expressway nodes, major road sections, and transportation hubs to ensure reasonable distribution and maximum utilization of the charging facilities. In addition, operators should strengthen the construction of basic service facilities such as restaurants, restrooms, resting chairs et al., which make users feel content while waiting for charging. Besides, more attention should be given to younger BEV users and those who travel less frequently on expressways, the results of multi-group analysis show that these two groups of users do not have strong attitudes toward charging in the service areas. Operators could set corresponding price discounts or lotteries for BEV users who have charged in the service area multiple times to attract young users and users with less frequent expressway travel. The above suggestions can not only make users have a positive attitude toward infrastructures launched on expressways but also increase users' willingness to drive BEVs on expressways, thereby accelerating the realization of road decarburization goals.

The subjective norms positively impact BEV users' reuse intention. This is a clear indication that external information from family, friends, or news media greatly influences BEV users in reusing charging infrastructures of service areas. Therefore, operators should adopt strategies to improve the word-of-mouth of charging infrastructures in service areas. For example, optimizing the user interface and interaction design to ensure easy and intuitive operation, and providing multi-language support and barrier-free services so that users with different backgrounds and needs can use it easily. Besides, hybrid energy source systems play a key role in supplying energy to EVs (Zhang et al. 2023). Therefore, powering charging infrastructures on expressways based on renewable energy systems such as solar or wind energy, which is beneficial to demonstrate their environmental protection advantages to the public. Furthermore, service area operators can implement a "rewarded referral policy" (Liu et al. 2023), which means if an existing user invites a new user to charge in the service area, then both parties will have a corresponding price discount. This policy will serve the purpose of publicizing the charging infrastructures in the service area, thus further increasing the intention to recharge. According to the results of multi-group analysis, the subjective norm has a more significant effect on reuse intention among users with low expressway travel frequency. Thus, a threshold-based charging incentive policy for EV users could be implemented. For instance, if the EV user reaches the specified number of charging times in the expressway service area within the corresponding period, they will receive the corresponding monetary reward. These incentive measures could be effective in attracting users with low highway travel frequency to charge in the service area.

Although the positive impact of perceived behavioral control on reuse intention is not statistically significant, we believe this finding can still provide practical advice to marketers and operators. The number of staff in the charging infrastructures should be appropriately increased to guide users on-site during the charging process and respond to some emergencies. In addition, when there are more BEV users in the service area, queue jumping is likely to occur. Therefore, it is recommended to design a mobile app to allocate charging piles for BEV users in an orderly manner. This can improve charging efficiency and avoid energy waste during peak hours, which is beneficial for sustainable energy development and ecological environment protection.

Given the negative effects of perceived risk, several specific measures should be implemented to reduce it during the charging process in expressway service areas. Insurance policies could be formulated to compensate BEV users for possible losses related to charging in service areas, such as battery damage caused by the charging infrastructures in service areas. Meanwhile, the government should also formulate uniform standards and specifications for the charging piles to ensure their safety and reliability. Besides, staff should be regularly arranged to inspect and repair the charging infrastructures in the expressway service area to reduce the damage rate of charging piles and improve the charging experience. Furthermore, the scheduled charging system should be introduced to allow users to reserve charging time slots and charging piles in advance to avoid waiting too long when they arrive at the service area and delaying subsequent travel plans. Finally, the survey also shows that some users are worried about the high cost of charging on expressways or that their payment information will be stolen. Therefore, operators should clarify and disclose the charging standards and structure of charging fees, and provide a variety of convenient payment methods, such as electronic payment, mobile payment, prepaid card, plug and charge, etc., to meet the payment habits and needs of different users. The above suggestions can effectively reduce users' perceived risks, which can also attract more potential users who are worried about some problems when charging on the expressway to buy BEV, thereby contributing significantly to road decarburization.

6.2. Limitations and future research

This study has certain limitations: Firstly, while the sample size matches prior research' suggested requirements, the generalizability of the model conclusions should be taken with caution. Future studies could appropriately expand the sample population. Secondly, the study does not consider the variables influencing EV adoption and charging behavior, such as infrastructure accessibility and charging costs. Third, this study targeted BEV users who have experienced charging in expressway service areas, future research could focus on those who do not have an expressway travel experience to explore their charging intention. In addition, some PHEV users also choose to increase their travel range by charging (Ge, MacKenzie, and Keith 2018), so subsequent researchers could analyze the factors affecting PHEV charging in the service area and compare the differences between the two user groups. It will be interesting to explore the spatiotemporal patterns of charging demand and predict the charging demand of EV users based on historical charging data of EVs in the expressway service area, and then propose the charging station location model and configuration optimization model for charging infrastructures on the expressway. Moreover, battery swapping is an emerging technology for increasing the cruising range of EVs. Compared with traditional pile charging, battery swapping is highly efficient. Meanwhile, battery swap stations have begun to be deployed in urban areas or on expressways (EBSN Expressway Battery Switching Networks 2023), so future work could explore the battery swap behaviors of EV users.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

This work was supported by the National Natural Science Foundation of China [grant numbers 52202387, 52372301, 52172304]; the Science and Technology Project of Hebei Education Department [grant number BJK2022044].

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